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RESEARCH ARTICLE

Investment momentum: A two-dimensional behavioural strategy

Fangming Xu[1] | **Huainan Zhao**[2] | **Liyi Zheng**[1]

[1]School of Accounting and Finance, University of Bristol, Bristol, UK

[2]School of Business and Economics, Loughborough University, Loughborough, UK

Correspondence
Liyi Zheng, School of Accounting and Finance, University of Bristol, Bristol, UK.
Email: liyi.zheng@bristol.ac.uk

Abstract

We propose an investment-momentum strategy of buying past winners with low investment and selling past losers with high investment, which simultaneously exploits two dimensions of market inefficiencies. The new strategy generates twice the monthly returns earned by either the price momentum or investment strategy (1.44% vs. 0.75% or 0.61%). Despite the diminishing anomalies in recent decades, the investment-momentum stays persistent. The mispricing-based strategy performs better in periods of high investor sentiment or for stocks with high limits-to-arbitrage, which is consistent with our expectations. Overall, we show that one can simultaneously use multiple dimensions of market inefficiency to attain superior performance.

KEYWORDS

behavioural finance, corporate investment, investment momentum, mispricing, price momentum

1 | INTRODUCTION

Price momentum is pervasive and has been observed across periods (Chan, Jegadeesh, & Lakonishok, 1996; Jegadeesh & Titman, 1993, 2001), countries (Griffin, Ji, & Martin, 2004; Rouwenhorst, 1998), and markets (Asness, Moskowitz, & Pedersen, 2013; Menkhoff, Sarno, Schmeling, & Schrimpf, 2012). In light of its remarkable success, it is logical to question: Should 'momentum traders' care about any corporate fundamentals, like investments? Given their trading strategy *solely* based on past stock returns and 'arbitrage away any under-reaction left behind by the newswatchers' (Hong & Stein, 1999, p. 2145), it seems unnecessary for them to consider anything other than past prices.[1]

With respect to this question, Baker, Stein, and Wurgler (2003) and Polk and Sapienza (2009) show that stock market mispricing influences firms' investment and 'firms that overinvest are overpriced' (Polk & Sapienza, 2009, p. 188), implying that a firm's level of investment serves as a (partial) indication of its (mis)valuation.[2] If the *mispricing* indicated by investment is fully captured by the price momentum, then the investment should have no added value to momentum traders. If this is not the case, then it is likely to add incremental value to momentum traders and, hence, an opportunity for them to arbitrage away, over and above, any underreaction left behind by the newswatchers.[3]

In this paper, we develop a two-dimensional behavioural strategy by combining price momentum and capital investment[4] to explore the multiple dimensions of market inefficiency simultaneously. Our *investment-momentum* (*InvMom*) strategy also seems to be supported by the evidence from Hou et al. (2020) who classify 452 documented anomalies into six broad categories (i.e., momentum, value-versus-growth, investment, profitability, intangibles,

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and trading frictions) and show that the two strongest anomalies are the investment and momentum anomalies. Thus, combining investment and momentum is likely to generate superior performance by taking advantage of the two most prominent dimensions of market inefficiency/mispricing, if the two strategies carry an incremental or independent information set.

Overall, our InvMom strategy of buying past winners with low investment and selling past losers with high investment generates about *twice* the monthly returns earned by either the momentum or investment strategy alone (1.44% vs. 0.75% or 0.61%, respectively) between 1965 and 2015. Further, when the momentum or investment strategy exhibits insignificant performance during the later stage of the sample (2000–2015),[5] the investment momentum produces persistent results. Hence, the investment momentum is stronger and more persistent than the momentum or investment strategy alone (Figure 1).

Recognising that mispriced stocks influence firms' investment decisions through *equity financing* and *catering* channels (Baker et al., 2003; Polk & Sapienza, 2009), we conjecture that the incremental value of corporate investment for a momentum trader should be higher when the conditions are more favourable for the two channels to function.[6] Baker et al. (2003) show that firms' investment decisions are affected by stock mispricing via the equity financing channel. They interpret that managers prefer issuing overvalued stocks to fund investments and are less likely to fund investments if they have to issue undervalued stocks. Polk and Sapienza (2009) present an alternative explanation of the positive relationship between firms' investment and stock mispricing, that is, the catering channel. They argue that managers cater to investors by accepting some negative investment opportunities when stocks are overvalued.[7] Both channels suggest that firms are more likely to overinvest when their stocks are overpriced, through issuing overpriced shares or catering to the current market sentiment. Hence, the level of corporate investment serves as a good indicator of the degree of mispricing and, therefore, lends more incremental information to the momentum traders.

Following the identification strategies of Baker et al. (2003) and Polk and Sapienza (2009), we show that the investment momentum generates the strongest results when conditions are most favourable for the equity financing and catering channels to work. This confirms our conjecture and, to some extent, helps us understand why and how the investment momentum generates enhanced performance.

Further, our mispricing-based InvMom strategy should work better, or the investment-momentum anomaly should be more pronounced when the investor sentiment is high or limits to arbitrage are severe (Baker & Wurgler, 2007; Jacobs, 2015). We use the Baker and Wurgler (2006) sentiment index and the University of Michigan consumer sentiment index to gauge investor sentiment, bid-ask spread, institutional ownership, and idiosyncratic volatility to measure the degree of the limits to arbitrage. We find that the investment momentum is more pronounced in periods of high investor sentiment or for stocks subject to high limits to arbitrage, which further confirms our multi-dimensional mispricing approach.

We conduct a series of robustness checks to test our results. We show that the superior performance of the

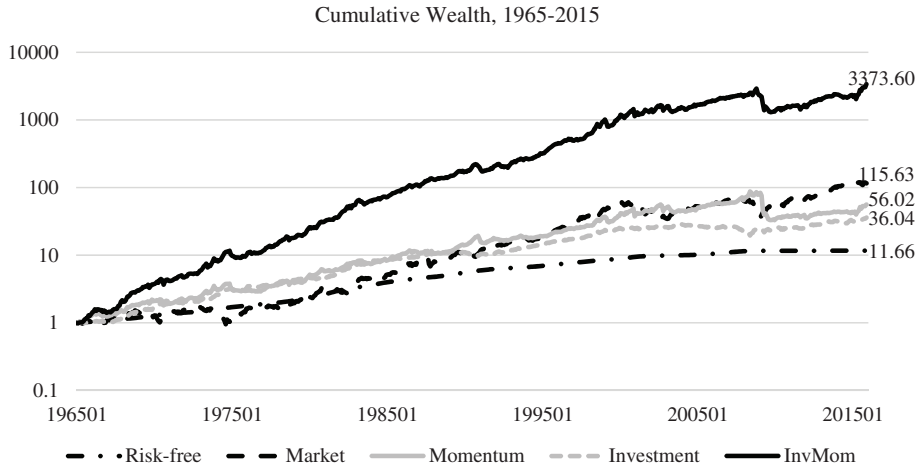

FIGURE 1 Investment-Momentum Strategy, 1965–2015. This figure shows the cumulative wealth of investing $1 in 1965 and holding it until 2015 by following five different strategies: (1) investing in the risk-free asset; (2) investing in the CRSP value-weighted index; (3) the momentum strategy of buying past winners and shorting past losers; (4) the investment strategy of buying low investment stocks and shorting high investment stocks; and (5) the investment-momentum strategy (InvMom) of buying winner stocks with low investment and shorting loser stocks with high investment. The numbers reported in the figure are dollars

InvMom strategy, compared to either the momentum or investment strategy, is not driven by the size effect. We further show that our finding is not subject to how we construct our portfolios and how we measure their performance. Apart from using raw returns, we further employed characteristic-adjusted returns and standard asset pricing models, such as the Fama–French three- and five-factor models to adjust for risk.[8] Our results are consistent throughout the tests.

Our paper relates to a string of studies in the momentum literature, which explore the incremental value of corporate *fundamentals* in the traditional price-momentum strategy. Prior studies have identified some firm fundamentals/characteristics that strengthen the price momentum, such as firm size and analyst coverage (Brennan, Jegadeesh, & Swaminathan, 1993; Chen & Zhao, 2012; Hong, Lim, & Stein, 2002; Zhang, 2006), earnings (Chan et al., 1996; Chordia & Shivakumar, 2006), book-to-market ratio (Asness et al., 2013; Daniel & Titman, 1999), turnover (Lee & Swaminathan, 2000), idiosyncratic return volatility (Chichernea & Slezak, 2013; Zhang, 2006), revenues, costs, and real options (Sagi & Seasholes, 2007), dividend payments (Asem, 2009), and, recently, seven major fundamentals to take advantage of big data (Huang, Zhang, Zhou, & Zhu, 2019).

The objective of our study is not to document another enhanced momentum strategy based on identifying any new fundamentals or combining them[9] but to show that market inefficiency/mispricing has many dimensions that we can jointly exploit. After all, as Mclean and Pontiff (2016, p. 8) argue '...mispricing accounting for some or all of the original return predictability'; thus, treating mispricing as an alternative to fundamentals would expand our investment dimension and earn potential superior returns. Nevertheless, we try to set an example by showing that one can simultaneously use multiple dimensions of market inefficiency to learn about (and profit from) future stock returns. Our paper further shows that a combined strategy generates hedging value to individual strategies which provide double returns but no doubled standard deviations across different market conditions.

The remainder of the paper is organized as follows. Section 2 describes the data and the methodologies in forming the portfolio strategies. Section 3 reports the empirical results and conducts the robustness test. Section 4 concludes the paper.

2 | DATA AND METHODOLOGY

Our sample consists of common stocks (share codes 10 and 11) traded on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) for the period from January 1965 to December 2015. Monthly stock returns are collected from the Center for Research in Security Prices (CRSP), and accounting data used to construct investment strategies is obtained from the Compustat.

We follow Jegadeesh and Titman (1993) in constructing the price momentum strategy. Specifically, at the end of each month (Month 0), we rank all stocks based on their past 6-month returns (from Month −5 to Month 0) and sort them into quintiles. We then take a long position in the winner portfolio and a short position in the loser portfolio and hold it for 6 months (from Month 2 to Month 7). In line with the literature (Asness et al., 2013; Daniel & Moskowitz, 2016; Fama & French, 1996), we skip Month 1 to avoid short-term reversals due to microstructure issues, as suggested by Jegadeesh (1990), Lehmann (1990), and Grinblatt and Moskowitz (2004). Stocks priced less than \$5 at the beginning of the holding period are excluded from the sample to prevent results from being driven primarily by small and illiquid stocks (Antoniou, Doukas, & Subrahmanyam, 2013; Cooper, Gutierrez, & Hameed, 2004; Jegadeesh & Titman, 2001).

We follow Lyandres et al. (2008) in forming the investment strategy.[10] Specifically, we measure the investment-to-asset (I/A) ratio as the annual change in gross property, plant, and equipment plus the annual change in inventories divided by the lagged book value of assets. At the end of each month, we rank all stocks based on their I/A ratios reported in the most recent annual financial statement and sort them into quintiles. We then take a long position in the low investment portfolio and a short position in the high investment portfolio and hold it for 6 months (from Month 2 to Month 7).

To construct the InvMom strategy, we combine past returns and I/A ratios. Specifically, at the end of each month, we sort stocks independently into quintiles based on their past 6-month returns and their latest I/A ratios,[11] respectively. This independent double-sorting procedure generates 5×5 combinations of momentum and investment portfolios. We form the InvMom strategy by taking a long position in the winner portfolio with low investment and a short position in the loser portfolio with high investment and hold them for the next 6 months (from Month 2 to Month 7). Throughout the paper, we test and compare the performance between the InvMom strategy and the individual strategy.

3 | EMPIRICAL RESULTS

In this section, we first present the key empirical results and test the persistence of the results. We next use the equity financing and catering channels to show the inner workings of the InvMom strategy in an attempt to gain a

better understanding of the two-dimensional strategy. We then show that our behavioural-based approach indeed works better when mispricing is more severe, such as in periods of high investor sentiment or for stocks subject to high limits to arbitrage. Finally, we submit our results to a battery of robustness tests, including using different portfolio sorting and weighting methods, adjusting for key firm characteristics, and applying alternative asset pricing models in our estimation.

3.1 | Momentum, investment, and investment-momentum strategies

We first test the momentum and investment strategies for our full sample (1965–2015) separately. Consistent with the literature, Panel A of Table 1 shows that past winners significantly outperform past losers by 0.75% ($t = 4.25$) per month, and stocks with low capital investment outperform high-investment stocks by 0.61% ($t = 6.80$) per month.[12]

Since both trading strategies are based on publicly available information and both generate significant abnormal returns, this indicates market inefficiency/mispricing in both dimensions. However, it is not clear whether one strategy dominates or subsumes the other, or whether both have reliable independent predictive power. Thus, we examine the interaction effect between these two dimensions.

Using the independent double-sorting method, we construct 25 portfolios (5×5) based on past stock returns and the latest I/A ratios. As seen in Panel B, the momentum strategy generates a return of 0.70% ($t = 3.41$) per month under low investment and 1.04% ($t = 5.53$) per month under high investment. Nyberg and Pöyry (2014) documented similar findings that the momentum effect is strongest for the group of firms with the highest asset growth. The investment strategy produces a return of 0.74% ($t = 5.52$) per month for loser stocks and 0.40% ($t = 3.34$) per month for winner stocks. Hence, economically and statistically significant returns are generated by following one strategy while the other is controlled for. This suggests that neither the momentum nor the investment is capable of explaining or subsuming the other, and each seems to carry unique information and should have incremental power to enhance each other's performance.

Next, we combine the two distinct dimensions of market inefficiencies to explore the potential joint effects and enhanced performance. Specifically, we form our InvMom strategy by longing past winners with low investment and shorting past losers with high investment. Results in Panel C show that the InvMom strategy generates a monthly return of 1.44% ($t = 7.54$), which doubles the returns generated by either the momentum (0.75% per month) or the investment strategy (0.61% per month), and the differences in the returns are highly significant with *t*-values above 5.

Harvey, Liu, and Zhu (2016) propose *t*-value cutoffs of 2.78 and 3.39 and argue that a newly discovered factor should have a *t*-value above 3. Hou et al. (2020) show that imposing a *t*-value cutoff of 2.78 increases the proportion of insignificant anomalies to 82%. Our InvMom strategy generates a monthly return of 1.44% with a *t*-value above 7, which is superior to either the momentum or investment strategy and demonstrates the power of the two-dimensional strategy.

To better visualize the performance of the investment momentum relative to the individual strategies, in Figure 1, we plot the cumulative wealth of investing $1 in 1965 and holding it until 2015 by following five different strategies: (a) investing in the risk-free asset, (b) investing in the CRSP value-weighted index, (c) investing in the momentum strategy of buying past winners and selling past losers, (d) investing in the investment strategy of buying low investment stocks and shorting high investment stocks, and (e) investing in the InvMom strategy of buying winner stocks with low investment and shorting loser stocks with high investment. As seen, the InvMom strategy comfortably beats all the other strategies right from the beginning, and the compounding effect is rather extraordinary for the investment momentum, which leads to superior performance for the past 50 years (1965–2015).

Since the markets have gone through many bull and bear periods during our 50-year sample period, it would be interesting to see how the InvMom strategy performs under different market conditions. In the spirit of Novy-Marx (2013), we assess the hedge value of the InvMom strategy by measuring its performance against its standard deviations and doing it also for the bull and bear markets, respectively. In particular, we compare the annualized portfolio returns and the Sharpe ratios of the combined strategy with that of the individual strategy (i.e., momentum or investment) over the entire sample period and the sub-periods of bull and bear markets. The bull and bear turning points are determined by Bry and Boschan's (1971) dating method based on the S&P 500 index.[13]

In Table 2, we show that the combined InvMom strategy produces annualized returns twice as large as the individual strategies without encountering a significant increase of standard deviations for the whole sample period. It also holds for the sub-samples of bull and bear markets: the annualized returns (and the Sharpe ratios) of the combined strategy is about twice as large, while the standard deviations are only marginally larger. These results demonstrate the persistence of the InvMom

TABLE 1 Momentum, investment, and investment-momentum strategies, 1965–2015

Panel A: Single sort on past returns or I/A ratios					
	Momentum portfolios			**Investment portfolios**	
	(Past returns)			**(I/A ratios)**	
Loser	0.09%	[0.28]	Low	0.80%	[2.99]
Winner	0.84%	[3.26]	High	0.19%	[0.67]
Winner-loser	*0.75%*	*[4.25]*	*Low-high*	*0.61%*	*[6.80]*

Panel B: Independent double sort by past returns and I/A ratios						
	I/A ratios					
Past returns	Low		High		*Low-high*	
Loser	0.32%	[0.89]	−0.42%	[−1.26]	*0.74%*	*[5.52]*
Winner	1.02%	[3.62]	0.62%	[2.15]	*0.40%*	*[3.34]*
Winner-loser	*0.70%*	*[3.41]*	*1.04%*	*[5.53]*		

Panel C: Investment-momentum (InvMom)		
InvMom	*1.44%*	*[7.54]*
InvMom versus momentum	0.69%	[7.15]
InvMom versus investment	0.83%	[5.10]

Note: This table reports the average monthly returns of portfolios formed on past stock returns or/and capital investment using common stocks traded on the NYSE/AMEX between 1965 and 2015. At the end of each month, stocks are ranked based on their past 6-month monthly stock returns or their latest annual investment-to-asset (I/A) ratio and sorted into quintiles. Loser (Low) consists of stocks with the lowest past 6-month returns (latest I/A ratios), while Winner (High) consists of stocks with the highest past 6-month returns (latest I/A ratios). In Panel A, the average monthly returns of loser and winner portfolios are reported, along with the raw profits of the momentum portfolios (Winner–Loser) and the investment portfolios (Low–High). In Panel B, stocks are sorted independently into quintiles based on past 6-month returns and their latest I/A ratios. The intersections resulting from the two independent sorts generate 5 × 5 investment and momentum portfolios. In Panel C, the investment-momentum (*InvMom*) strategy involves buying past winner stocks with low investment and shorting loser stocks with high investment. Stocks with prices below $5 are excluded from the sample. For all portfolios, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted t-statistics are shown in brackets.

TABLE 2 Performance of the Investment-Momentum Strategy across Market Conditions

	Full sample			**Bear markets**			**Bull markets**		
	Return	***SD***	**Sharpe ratio**	**Return**	***SD***	**Sharpe ratio**	**Return**	***SD***	**Sharpe ratio**
Momentum	9.38%	0.14	0.66	7.46%	0.13	0.55	15.67%	0.16	0.98
Investment	7.56%	0.07	1.05	5.94%	0.07	0.89	12.85%	0.09	1.50
InvMom	18.74%	0.16	1.21	16.15%	0.15	1.09	27.31%	0.18	1.55

Note: This table shows the annualized returns, annualized standard deviation (*SD*), and annualized Sharpe ratio of the momentum strategy (buying past winners and shorting past losers), the investment strategy (buying low investment stocks and shorting high investment stocks), and the investment-momentum strategy (buying winner stocks with low investment and shorting loser stocks with high investment) from 1965 to 2015. The annualized Sharpe ratio is estimated as the annualized monthly average excess returns divided by the annualized monthly standard deviation. The bear market periods over our whole sample period include: February 1966–September 1966; December 1968–June 1970; January 1973–September 1974; January 1977–February 1978; December 1980–July 1982; July 1983–May 1984; September 1987–November 1987; June 1990–October 1990; September 2000–February 2003; November 2007–February 2009, and the remaining periods are classified as bull market periods.

TABLE 3 Persistence of the investment-momentum strategy

	1965–1989		1990–2015	
Momentum	0.95%	[4.95]	0.55%	[1.91]
Investment	0.83%	[6.72]	0.40%	[3.24]
InvMom	*1.83%*	*[8.15]*	*1.07%*	*[3.60]*
InvMom versus momentum	0.87%	[7.47]	0.52%	[3.50]
InvMom versus investment	1.00%	[5.50]	0.67%	[2.52]
	1990–1999		**2000–2015**	
Momentum	0.86%	[2.58]	0.37%	[0.88]
Investment	0.67%	[4.09]	0.23%	[1.38]
InvMom	*1.57%*	*[3.65]*	*0.76%*	*[1.96]*
InvMom versus momentum	0.71%	[3.33]	0.40%	[2.01]
InvMom versus investment	0.90%	[2.44]	0.53%	[1.47]

Note: This table reports the monthly returns of the investment-momentum strategy across different periods. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. Stocks are divided into four sub-periods. Within each period, the momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks, and the investment momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

strategy despite different market conditions; especially, it serves as a hedge against tough market conditions (i.e., the bear markets).

3.2 | Persistence of the investment-momentum strategy

Recent papers show that the momentum effect has gradually disappeared over the last decade or so.[14] Mclean and Pontiff (2016) argue that the phenomenon of diminishing anomalies has mainly been caused by the increasing awareness of investors about mispricing from academic publications, and they report that the average predictor's abnormal returns shrink 58% post-publication. How persistent is the InvMom strategy? In Table 3, we conduct a sub-period analysis to test the persistence of the InvMom strategy along with other individual strategies.

Consistent with the literature, we observe a similar pattern of diminishing returns under either the momentum or investment strategy. The momentum strategy was particularly strong both economically and statistically in the first 25 years of the sample (1965–1989), whereas it reduces to 0.55% per month (dropping by nearly half compared to the first period) and becomes statistically insignificant at the 5% level during the second 25-year period (1990–2015). In comparison, although the InvMom strategy also exhibits relatively weaker performance in the second period, it generates 1.07% ($t = 3.60$) per month for this period. During the most recent 15 years (2000–2015), neither the momentum nor the investment strategy produces any statistically significant returns, whereas the InvMom strategy still earns 0.76% per month, although it is reduced to the 5% significance level.

Mclean and Pontiff (2016, p. 7) argue 'If return predictability reflects mispricing and publication leads sophisticated investors to learn about and trade against the mispricing, then we expect the returns associated with a predictor should disappear or at least decay after the paper is published'. Since both the momentum and investment anomalies have been well documented in the literature, it should be no surprise that investors have exploited these one-dimensional mispricing strategies. Hence, turning to multiple dimensions of market inefficiency is necessary to obtain and maintain persistent performance, which is what we advocate in this paper.

3.3 | Investment-momentum: Equity financing and catering channels

Baker et al. (2003) and Polk and Sapienza (2009) show that mispricing stocks affect firms' investment decisions through either the equity financing channel or the catering channel. The equity financing channel has been developed by a series of studies including, for example, Morck, Shleifer, and Vishny (1990), Blanchard, Rhee,

and Summers (1993), and Stein (1996). Among these studies, Stein (1996) is closely related to the work of Baker et al. (2003). The model in Stein (1996) implies that firms that need external equity to finance their marginal investments are especially sensitive to the non-fundamental component of stock prices (i.e., mispricing). Specifically, in contrast to financially flexible firms that can insulate their investment decisions from irrational movements in stock prices, an equity-dependent firm is less likely to proceed with its capital investment if it has to issue undervalued shares. Baker et al. (2003) utilise a simplified version of the model in Stein (1996) to derive several testable hypotheses that are unique to the specific equity financing channel. Their model prediction and empirical tests indicate that stock prices have a more substantial impact on the investment of equity-dependent firms (i.e., firms that need external equity to fund marginal investments).

To understand the impact of stock market mispricing on firms' investment policy, Polk and Sapienza (2009) consider an alternative channel—the catering theory.[15] They argue that managers may try to misallocate investment capital to boost short-run share prices if stock markets misprice firms according to their investment levels. For example, firms may invest in value-destroying projects (forgo positive investment opportunities) when their stock is overvalued (undervalued).

We conjecture that the incremental value of corporate investment to a momentum trader should be more pronounced when the conditions are more favourable for the two channels to function. Both the equity financing channel and the catering channel suggests that firms are more likely to overinvest when its stock price is overvalued, either to take advantage of issuing overpriced shares or to cater the current market sentiment. Hence, the level of corporate investment serves as a good indicator of the degree of mispricing and, therefore, lends more incremental information to the momentum traders.

The equity financing channel works better for equity-dependent firms, which tend to be young firms with strong investment opportunities, but with low cash balances and high cash-flow volatility (Baker et al., 2003). The Kaplan and Zingales (1997) index of financial constraints satisfies most of these criteria and, therefore, is employed in Baker et al. (2003) to measure firms' equity dependence.[16] Kaplan and Zingales (1997) classify firms into discrete categories of financial constraints using both subjective and objective criteria and then relate their qualitative ranking to five accounting ratios using an ordered logit regression. The regression parameters allow one to create a synthetic KZ index of financial constraints (Baker et al., 2003; Lamont, Polk, & Saaá-Requejo, 2001). Following these studies, we construct the five-variable KZ index using the following linear model:

$$KZ_{it} = -1.002\frac{CF_{it}}{A_{it-1}} - 39.368\frac{DIV_{it}}{A_{it-1}} - 1.315\frac{C_{it}}{A_{it-1}} + 3.139LEV_{it} + 0.283Q_{it}$$

where CF_{it}/A_{it-1} is cash flow over lagged total assets; DIV_{it}/A_{it-1} is cash dividends over lagged assets; C_{it}/A_{it-1} is cash balances over lagged assets; LEV_{it} is leverage; and Q is the market value of equity plus assets minus the book value of equity scaled by lagged assets.

The catering channel works better for more opaque firms, which is measured by the research and development (R&D) intensity of the firm (Polk & Sapienza, 2009). Firms with higher (lower) R&D intensity is considered to be more opaque (transparent), based on the assumption that it is more difficult and time-consuming to resolute all valuation uncertainty for R&D projects than for other types of projects. R&D intensity is measured as total R&D expenses over lagged total assets. We test whether the InvMom strategy is more pronounced when the conditions are more favourable for the two channels to function (i.e., when corporate investment carries more incremental information of mispricing).

In Panel A of Table 4, we first sort and equally divided stocks into high, medium, and low groups based on the KZ index. We then test all three strategies within each group. The InvMom strategy generates a significant return of 1.75% ($t = 4.75$) per month for more equity-dependent firms compared to 0.95% ($t = 3.47$) per month for less equity-dependent firms. Similarly, in Panel B, we first sort and equally divided stocks into high, medium, and low groups based on the R&D intensity. We then perform the three strategies. As expected, the InvMom strategy generates a return of 1.62% ($t = 4.83$) per month for more opaque firms compared to 1.06 ($t = 3.10$) per month for less opaque firms. Overall, these results are consistent with our conjecture and helped us gain a better understanding of why and how the InvMom strategy generates superior performance.

3.4 | Investor sentiment and limits to arbitrage

Our analysis, so far, shows that the two-dimensional strategy outperforms the individual strategy. Since our InvMom strategy is based on multiple dimensions of market inefficiency, it should generate better performance when mispricing is more acute, such as in periods of high

TABLE 4 Investment-momentum: The 'equity financing' and 'catering' channels

Panel A: The 'equity financing' channel: Equity dependent/financial constraints						
	High		**Medium**		**Low**	
Momentum	0.98%	[3.85]	0.62%	[3.11]	0.47%	[2.78]
Investment	0.53%	[2.49]	0.72%	[5.13]	0.50%	[3.45]
InvMom	*1.75%*	*[4.75]*	*1.20%*	*[4.00]*	*0.95%*	*[3.47]*
InvMom versus momentum	0.77%	[2.48]	0.59%	[2.77]	0.48%	[2.06]
InvMom versus investment	1.22%	[3.84]	0.48%	[1.94]	0.45%	[2.07]
Panel B: The 'catering' channel: R&D intensity						
	High		**Medium**		**Low**	
Momentum	0.71%	[3.18]	0.64%	[3.22]	0.56%	[2.64]
Investment	0.69%	[3.52]	0.77%	[5.38]	0.53%	[2.69]
InvMom	*1.62%*	*[4.83]*	*1.60%*	*[5.99]*	*1.06%*	*[3.10]*
InvMom versus momentum	0.91%	[3.39]	0.95%	[4.26]	0.50%	[1.94]
InvMom versus investment	0.93%	[3.08]	0.83%	[3.58]	0.53%	[1.71]

Note: This table tests the investment-momentum strategy via the 'equity financing' and 'catering' channels. Equity dependent/financial constraints are measured by the KZ index of Kaplan and Zingales (1997). R&D intensity is measured as firms' annual R&D expenses scaled by the lagged book value of assets. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. All stocks are equally divided (i.e., 1/3) into high, medium, and low groups based on the KZ index or R&D intensity. Within each group, the momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks; and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

investor sentiment or for stocks subject to more severe limits to arbitrage.

3.4.1 | Investor sentiment and investment momentum

Prior studies have shown that investor sentiment plays a significant role in explaining asset pricing anomalies (Baker & Wurgler, 2006; Baker, Wurgler, and Yuan, 2012; Lemmon & Portniaguina, 2006; Hribar & McInnis, 2012; Seybert & Yang, 2012; Stambaugh, Yu, & Yuan, 2012, 2014; Firth, Wang, & Wong, 2014). Generally, during high-sentiment periods, the optimistic views tend to be overly optimistic, and stocks are likely to be overpriced. During low-sentiment periods, the optimistic views tend to be more realistic, and stocks are likely to be more correctly priced. Consequently, anomalies should be more pronounced during high-sentiment periods.

We conjecture that the investment-momentum anomaly should be more pronounced in periods of high investor sentiment. In Table 5, we sort and equally divided stocks into high, medium, and low sentiment periods based on the Baker and Wurgler (2006) sentiment index (Panel A) and the University of Michigan consumer sentiment index (Panel B).[17] Our results show that the InvMom strategy is both economically and statistically stronger in high-sentiment periods than in low-sentiment periods. For instance, using the University of Michigan sentiment measure (Panel B), the InvMom strategy generates a monthly return of 1.80% ($t = 7.47$) in high-sentiment periods compared to 0.99% ($t = 3.10$) in low-sentiment periods.

Overall, the results in Table 5 are consistent with our conjecture that the investment-momentum anomaly is more pronounced in periods of high investor sentiment, in which the mispricing is more severe.

3.4.2 | Limits to arbitrage and investment momentum

We next examine how the InvMom strategy performs under different levels of limits to arbitrage. Prior studies show that limits to arbitrage can prevent the effectiveness

TABLE 5 Investor sentiment and investment-momentum

Panel A: Baker and Wurgler (2006) sentiment index						
	High		**Medium**		**Low**	
Momentum	**0.79%**	**[4.20]**	**0.77%**	**[2.65]**	**0.53%**	**[1.34]**
Investment	0.64%	[4.27]	0.40%	[2.82]	0.52%	[3.52]
InvMom	*1.47%*	*[6.11]*	*1.32%*	*[4.25]*	*1.25%*	*[3.18]*
InvMom versus momentum	0.67%	[4.32]	0.55%	[3.53]	0.72%	[4.42]
InvMom versus investment	0.83%	[4.26]	0.91%	[3.40]	0.73%	[2.14]
Panel B: University of Michigan Consumer sentiment index						
	High		**Medium**		**Low**	
Momentum	1.18%	[6.41]	0.82%	[5.06]	0.28%	[0.87]
Investment	0.51%	[4.79]	0.50%	[4.51]	0.65%	[4.44]
InvMom	*1.80%*	*[7.47]*	*1.32%*	*[6.52]*	*0.99%*	*[3.10]*
InvMom versus momentum	0.62%	[4.47]	0.51%	[3.68]	0.71%	[4.79]
InvMom versus investment	1.29%	[6.62]	0.82%	[4.79]	0.34%	[1.26]

Note: This table tests the investment-momentum strategy across different levels of investor sentiment. Investor sentiment is measured by Baker and Wurgler's (2006) investor sentiment index and the University of Michigan consumer sentiment index, respectively. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. All stocks are equally divided (i.e., 1/3) into high, medium, and low groups based on investor sentiment. Within each group, the momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks; and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

of rational arbitrageurs to 'undo the dislocations' caused by irrational investors (Barberis & Thaler, 2003; Brav & Heaton, 2002; Brav, Heaton, & Li, 2009; Doukas, Kim, & Pantzalis, 2010; Hirshleifer, 2001; Shleifer & Vishny, 1997). Given arbitrage is risky, costly, and limited, the investment-momentum anomaly should be more pronounced for stocks subject to high limits to arbitrage. To test this, we use three alternative measures for limits to arbitrage: the bid-ask spread, institutional ownership, and idiosyncratic volatility. Table 6 presents the results.

First, the bid-ask spread is estimated as the difference between the quoted ask and bid prices from the mid-quote on a particular day (Amihud & Mendelson, 1986). It represents compensation to the market maker or dealer for a round-trip transaction (purchase and sale). Stocks with high bid-ask spread are subject to higher limits to arbitrage than stocks with a low bid-ask spread. Panel A shows that all three strategies perform better in groups with a high bid-ask spread. The InvMom strategy generates a return of 2.13% per month under high bid-ask spread compared to 0.72% per month under low spread. It also clearly beats both the momentum and investment strategies no matter the level of the bid-ask spread.

Second, institutional ownership is related to the supply of stocks in the equity loan market (Dechow, Hutton, Meulbroek, & Sloan, 2001). Low institutional ownership implies a limited availability of stocks for borrowing and, thus, high short-selling costs. Following Nagel (2005), we use the percentage of institutional ownership (IO) divided by the number of shares outstanding to capture the costs of short selling. Panel B shows similar results. The InvMom strategy beats other strategies in all situations and generates a significant 1.67% per month under high institutional ownership compared to 0.96% per month under low institutional ownership.

Finally, idiosyncratic volatility as a measure of holding costs also captures the costs of arbitrage (Pontiff, 2006). Following Ang, Hodrick, Xing, and Zhang (2006) and Huang, Liu, Rhee, and Zhang (2009), we measure idiosyncratic volatility as the standard deviation of the residuals from the regressions of stock returns over the prior 12 months based on the Fama and French (1993) three-factor model. Panel C, again, shows consistent results. The InvMom strategy beats other strategies and generates a significant 2.07% per month under

TABLE 6 Limits-to-arbitrage and investment-momentum

Panel A: Limits-to-arbitrage measured by bid-ask spread						
	High		**Medium**		**Low**	
Momentum	1.15%	[4.78]	0.55%	[3.67]	0.37%	[3.64]
Investment	0.85%	[5.74]	0.48%	[5.07]	0.39%	[5.74]
InvMom	*2.13%*	*[7.58]*	*1.19%*	*[6.87]*	*0.72%*	*[5.24]*
InvMom versus momentum	0.98%	[5.17]	0.64%	[5.42]	0.34%	[3.90]
InvMom versus investment	1.28%	[5.32]	0.71%	[4.77]	0.33%	[2.78]
Panel B: Limits-to-arbitrage measured by institutional ownership						
	High		**Medium**		**Low**	
Momentum	1.15%	[4.78]	0.55%	[3.67]	0.37%	[3.64]
Investment	0.85%	[5.74]	0.48%	[5.07]	0.39%	[5.74]
InvMom	*2.13%*	*[7.58]*	*1.19%*	*[6.87]*	*0.72%*	*[5.24]*
InvMom versus momentum	0.98%	[5.17]	0.64%	[5.42]	0.34%	[3.90]
InvMom versus investment	1.28%	[5.32]	0.71%	[4.77]	0.33%	[2.78]
Panel C: Limits-to-arbitrage measured by idiosyncratic volatility						
	High		**Medium**		**Low**	
Momentum	1.09%	[4.53]	0.61%	[4.20]	0.28%	[2.58]
Investment	1.00%	[6.96]	0.54%	[5.19]	0.31%	[4.65]
InvMom	*2.07%*	*[7.15]*	*1.29%*	*[7.35]*	*0.60%*	*[5.11]*
InvMom versus momentum	0.98%	[4.97]	0.68%	[5.80]	0.32%	[4.03]
InvMom versus investment	1.07%	[4.34]	0.75%	[4.96]	0.29%	[2.61]

Note: This table tests the investment-momentum strategy under different levels of limits-to-arbitrage. The limits-to-arbitrage are measure by three proxies: bid-ask spread, institutional ownership, and idiosyncratic risk. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. All stocks are equally divided (i.e., 1/3) into high, medium, and low groups based on limits-to-arbitrage. Within each group, the momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks, and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

high idiosyncratic volatility compared to 0.60% per month under low idiosyncratic volatility.

Overall, Table 6 presents consistent results that the InvMom strategy performs better for stocks subject to high limits to arbitrage, and the two-dimensional strategy outperforms the investment and momentum strategies regardless of the level of limits to arbitrage.

3.5 | Robustness tests

In this subsection, we present a series of robustness tests on our results. We test our results across different size groups. We try alternative portfolio sorting and weighting methods in our estimations. We control for key firm characteristics, such as size, book-to-market, and industry, in measuring performance. In addition, we adjust for risk using different asset pricing models. In general, our results stand firm in these alternative tests.

3.5.1 | The performance of investment-momentum across different size groups

Our investment-momentum strategy may potentially be affected by the size effect. To investigate this, we run subsample tests by splitting firms into five size groups based on the NYSE size breakpoints. We re-estimate the profitability of the individual strategy (momentum or investment) and the combined InvMom strategy within each size group.

TABLE 7 Investment-momentum across different size groups

	ME1		ME2		ME3		ME4		ME5	
Momentum	0.97%	[3.89]	0.69%	[3.54]	0.59%	[3.26]	0.41%	[2.41]	0.32%	[2.13]
Investment	0.68%	[6.20]	0.65%	[5.34]	0.59%	[4.90]	0.36%	[3.19]	0.32%	[2.77]
InvMom	*1.91%*	*[7.62]*	*1.28%*	*[5.26]*	*1.34%*	*[5.88]*	*0.94%*	*[4.27]*	*0.72%*	*[3.91]*
InvMom versus momentum	0.94%	[4.89]	0.60%	[3.98]	0.76%	[4.66]	0.53%	[3.70]	0.39%	[3.34]
InvMom versus investment	1.23%	[5.58]	0.63%	[3.17]	0.75%	[3.77]	0.58%	[2.91]	0.40%	[2.21]

Note: This table tests the investment-momentum strategy across different size groups. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. All stocks are matched into appropriate size quintiles based on the NYSE 20%-size breakpoints. ME5 (ME1) represents the group with the largest (smallest) firms, where the firm size is measured by the market capitalization of stocks at the end of the formation period. Within each group, the momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks; and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

In Table 7, we show that the InvMom strategy generates significant positive monthly returns across all size groups. It outperforms twice as large as the individual strategy throughout the different size groups. This suggests that our enhanced investment-momentum strategy is implementable to a wide range of size groups and is not driven by the size effect.

3.5.2 | Robustness on alternative portfolio sorting and weighting methods

In Table 8, we present various robustness checks based on alternative estimation and portfolio sorting methods. First, we calculate the value-weighted raw returns. The InvMom strategy generates a value-weighted return of 1.09% ($t = 4.57$) per month, which beats the individual strategies by more than two times. Second, we change our portfolio formation method and form 10 momentum portfolios and 3 investment portfolios (10×3), instead of five momentum and five investment portfolios (5×5). Again, the InvMom strategy produces a return of 1.49% ($t = 6.14$) per month, which beats the other two strategies.

Third, we use alternative portfolio formation and holding periods. Instead of using the typical 6-month formation and 6-month holding period, we form portfolios based on a 12-month formation and 12-month holding period. The InvMom strategy generates a relatively lower return of 0.85% ($t = 4.53$) per month under the 12-month method compared to the 6-month method, although it still clearly outperforms the other individual strategies.

Finally, instead of using independent double sorting based on past 6-month stock returns and the latest I/A ratio, we test our results using sequential double sorting, where we first sort all stocks into quintiles based on their past 6-month returns, and then for each group, we further sort stocks into five portfolios based on their latest I/A ratios. The InvMom strategy generates a monthly return of 1.62% ($t = 7.71$) under the sequential double-sorting method. Thus, our results are not sensitive to different double-sorting methods.

3.5.3 | Robustness on characteristic-adjusted returns

In Table 9, we show the tested strategies by adjusting for the key firm characteristics, namely size, book-to-market, and industry. The size adjustment is based on size decile portfolios. We take the market value of equity as firm size, which is calculated as the closing price per share multiplied by the number of outstanding shares. The book-to-market adjustment is based on book-to-market decile portfolios. The book-to-market ratio is calculated using the book value of equity over the market value of equity at the end of the formation period.[18] The size and book-to-market adjustment are based on a 5×5 size and book-to-market portfolios. Stocks are matched to the appropriate size, book-to-market, or size and book-to-market portfolios.[19] The size-adjusted, book-to-market-adjusted, and size- and book-to-market-adjusted returns are calculated using the monthly return of the individual stock minus the monthly return of the appropriate benchmark portfolio.

We also adjust stock returns for their industry variations, as argued by Moskowitz and Grinblatt (1999), Pan, Liano, and Huang (2004), and Szakmary and Zhou (2015), who state that the momentum effect could be generated from the persistence of industry portfolio returns. Industry adjustment is based on the Fama and French 12-industry portfolios. The four-digit Standard Industrial Classification (SIC) codes provided by the CRSP are used for industry classification.[20] Stocks are matched to the

TABLE 8 Robustness on portfolio sorting and weighting

	Value-weighted raw returns		Ten price momentum and three I/A portfolios		Twelve months formation period and 12 months holding period		Sequential double sorting	
Momentum	0.45%	[2.27]	1.07%	[4.50]	0.35%	[1.94]	0.75%	[4.25]
Investment	0.40%	[3.34]	0.44%	[6.18]	0.50%	[5.79]	0.61%	[6.80]
InvMom	*1.09%*	*[4.57]*	*1.49%*	*[6.14]*	*0.85%*	*[4.53]*	*1.62%*	*[7.71]*
InvMom versus momentum	0.64%	[4.49]	0.42%	[4.29]	0.51%	[4.93]	0.87%	[7.98]
InvMom versus investment	0.69%	[3.12]	1.05%	[4.06]	0.35%	[2.04]	1.01%	[5.63]

Note: This table conducts robustness checks on the momentum, investment, and investment-momentum strategies based on different portfolio sorting and weighting methods. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. At the end of each month, stocks are ranked based on their past 6-month monthly stock returns or their latest annual investment-to-asset (I/A) ratio and sorted into quintiles. The intersections resulting from the two independent sorts generate 5 × 5 investment and momentum portfolios. The momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks, and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies (except the 12-month holding period), the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Columns 1 and 2 show the holding period returns based on the value-weighted average monthly raw returns. Columns 3 and 4 show average returns of intersecting portfolios of 10 price momentum and three investment-to-asset (I/A) ratios portfolios. Columns 5 and 6 shows average returns over 12-month holding periods (from Month 2 to 13) of portfolios formed based on 12-month formation periods (Month −11 to 0). Columns 7 and 8 show results use the sequential double sorting, where stocks are first sorted into quintiles based on their past 6-month returns and then further sorted into five equal groups based on their latest I/A ratios within each quintile. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

TABLE 9 Robustness on characteristic-adjusted returns

			Book-to-market		Size and book-to-market			
	Size-adjusted returns		Adjusted returns		Adjusted returns		Industry-adjusted returns	
Momentum	0.72%	[4.26]	0.82%	[4.94]	0.80%	[4.91]	0.69%	[4.34]
Investment	0.56%	[6.53]	0.50%	[5.90]	0.43%	[5.67]	0.58%	[7.36]
InvMom	*1.38%*	*[7.60]*	*1.40%*	*[7.52]*	*1.34%*	*[7.48]*	*1.33%*	*[7.57]*
InvMom versus momentum	0.66%	[7.20]	0.58%	[6.38]	0.53%	[5.98]	0.64%	[7.48]
InvMom versus investment	0.82%	[5.20]	0.89%	[5.70]	0.91%	[5.88]	0.75%	[5.17]

Note: This table tests the robustness of the momentum, investment, and investment-momentum strategies on characteristic-adjusted returns. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. At the end of each month, stocks are ranked based on their past 6-month monthly stock returns or their latest annual investment-to-asset (I/A) ratio and sorted into quintiles. The intersections resulting from the two independent sorts generate 5 × 5 investment and momentum portfolios. The momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks, and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Columns 1 and 2 use size-adjusted returns based on size decile portfolios. Firm size is measured as the market value of equity which equals closing share prices multiplied by the number of shares outstanding. Columns 3 and 4 use the book-to-market adjusted returns based on book-to-market decile portfolios. The book-to-market ratio is calculated using the book value of equity divided by the market value of equity at the end of the formation period. Columns 5 and 6 use size and book-to-market adjusted returns, which is based on **5 × 5** size and book-to-market portfolios. Columns 7 and 8 use the industry-adjusted returns, which is based on 12-industry portfolios defined using four-digit SIC codes from CRSP. The definition of 12-industry classification is obtained from Kenneth French's website. Stocks are matched with the appropriate industry portfolio, and the industry-adjusted returns are calculated using the monthly returns of the individual stock minus the monthly returns of the appropriate industry portfolio. Newey–West (1987) adjusted *t*-statistics are reported in brackets.

appropriate industry portfolio, and the industry-adjusted returns are calculated using the monthly return of the individual stock minus the monthly return of the appropriate industry portfolio.

Table 9 reports the characteristic-adjusted returns. As seen, the results are highly consistent across different adjustments. The InvMom strategy generates around 1.35% per month (compared to 1.44% per month using

the raw return) across the board, which is about twice as much as the returns earned by individual strategies. Overall, the characteristic adjustment does not affect our overall results.

3.5.4 | Robustness on risk-adjusted asset pricing models

We estimate the abnormal returns (alphas) for each trading strategy using four common asset pricing models to adjust for risk: the CAPM by Sharpe (1964), the Fama and French (1993) three-factor model, the Fama and French (2016) five-factor model, and the Pástor and Stambaugh (2003) liquidity-extended Fama–French three-factor model.[21] The asset pricing models used are listed below:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{MKT,t} + \varepsilon_{i,t},$$

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t},$$

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t},$$

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,mkt} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,p} f_{PSF,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the *month—t* return of portfolio i, $R_{f,t}$ is the risk-free rate for month t, $f_{MKT,t}$ is the month-t value of the market factor, $f_{SMB,t}$ is the month-t value of the Fama–French size factor, $f_{HML,t}$ is the month-t value of the Fama–French book-to-market factor, $f_{RMW,t}$ is the month-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the month-t value of the Fama–French investment factor, and $f_{PSF,t}$ is the month-t value of the Pástor–Stambaugh traded liquidity factor.[22]

Table 10 reports the estimated alphas (using monthly returns) for each trading strategy under the four different asset pricing models. The results are highly consistent across different benchmark models. For instance, under the Fama–French five-factor model, the InvMom strategy generates an alpha of 1.38% (t = 6.26) per month compared to 0.80% (t = 4.01) per month under the momentum strategy and 0.48% (t = 5.70) per month under the investment strategy. Overall, Table 10 presents consistent evidence that the InvMom strategy outperforms the investment and momentum strategy under all commonly used asset pricing models.

To test the overlapping part of the momentum/investment effects, we further conduct a spanning test following Novy-Marx (2015) and report the estimated alpha following Carhart's (1997) four-factor model and the I/A factor-extended Fama–French three-factor model.[23] We find that the investment effect cannot be fully captured by the momentum effect, where the estimated alpha of the investment strategy following Carhart's (1997) four-factor model remains significantly positive. We also find that the investment effect cannot entirely dominate the momentum effect because the estimated alpha of the

TABLE 10 Robustness on risk-adjusted asset pricing models

			Fama–French		Fama–French		Pástor–Stambaugh	
	CAPM		Three-factor model		Five-factor model		Liq. FF three-factor model	
Momentum	0.82%	[5.17]	0.96%	[6.41]	0.80%	[4.01]	1.17%	[7.16]
Investment	0.65%	[7.01]	0.52%	[5.79]	0.48%	[5.70]	0.53%	[5.04]
InvMom	*1.53%*	*[8.46]*	*1.53%*	*[8.22]*	*1.38%*	*[6.26]*	*1.77%*	*[8.59]*
InvMom versus momentum	0.72%	[7.20]	0.57%	[5.81]	0.59%	[6.05]	0.59%	[5.15]
InvMom versus investment	0.88%	[5.84]	1.01%	[6.66]	0.90%	[4.82]	1.24%	[7.25]

Note: This table tests the robustness of the momentum, investment, and investment-momentum strategies under commonly used asset pricing models. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. The table reports estimated regression alphas of monthly returns for the momentum, investment, and investment-momentum strategies under the following asset pricing models: the capital asset pricing model (CAPM), the Fama–French three- and five-factor model, the Pástor and Stambaugh (2003) liquidity-extended Fama–French three-factor model, the Carhart's (1997) four-factor model, and the I/A ratio extended Fama–French three-factor model. The sample includes all common stocks on the NYSE/AMEX with prices no less than $5 for the period 1965–2015. At the end of each month, stocks are ranked based on their past 6-month monthly stock returns or their latest annual investment-to-asset (I/A) ratio and sorted into quintiles. The intersections resulting from the two independent sorts generate 5 × 5 investment and momentum portfolios. The momentum strategy involves buying winner stocks and shorting loser stocks; the investment strategy involves buying low-investment stocks and shorting high-investment stocks, and the investment-momentum *(InvMom)* strategy involves buying winner stocks with low investment and shorting loser stocks with high investment. For all strategies, the holding period is 6 months, and there is a 1-month gap between the end of the formation period and the beginning of the holding period. Newey–West (1987) adjusted t-statistics are reported in brackets.

momentum strategy remains significantly positive following the Fama–French three-factor model with further control of the investment factor.

4 | CONCLUSION

Following the initial publication of the price-momentum strategy (Jegadeesh & Titman, 1993), a string of studies set out to discover enhanced or strengthened momentum strategies by identifying and combining firms' *fundamentals* with past stock returns to generate superior performance. This approach has indeed achieved considerable success. It is not difficult to understand why the focus has long been on fundamentals, as Huang et al. (2019) argue that 'academic research and education are almost entirely fundamentals'.

Instead of following this lead and documenting another fundamental-enhanced momentum strategy, in this paper, we investigate the non-fundamental component of stock prices (i.e., mispricing) and propose the InvMom strategy by simultaneously exploiting two dimensions of market inefficiency: the 'under-reaction left behind by the newswatchers' and the mispricing indicated by a firm's capital investment. Our choice of these two dimensions is supported by the fact that the investment and momentum anomalies are the two strongest anomalies of all (Hou et al., 2020). We conjecture that, if these two dimensions carry an independent and incremental information set of market inefficiencies, they should be able to reinforce each other and generate superior performance.

Empirically, we show that the InvMom strategy of buying past winners with low investment and short-selling past losers with high investment generates twice the monthly returns earned by either the price momentum or investment strategy (1.44% vs 0.75% or 0.61%) from 1965 to 2015. We find that, despite the diminishing/disappearing anomalies in recent decades (Mclean & Pontiff, 2016), the InvMom strategy stays persistent. We use the equity financing and catering channels to show the inner workings of the InvMom strategy. We find that the strategy works better when the conditions are more favourable for the two channels to function (i.e., when investment serves as a better indicator of mispricing and, hence, adds more incremental information to the price momentum). Given our approach is to take advantage of multiple dimensions of market inefficiency, it should perform better when mispricing is more acute. Indeed, we find that the investment-momentum anomaly is more pronounced in periods of high investor sentiment or for stocks subject to severe limits to arbitrage, which is consistent with our expectations. Overall, our study suggests that, in addition to identifying fundamental-enhanced momentum strategies, one can simultaneously use multiple dimensions of market inefficiency to arbitrage away over and above 'any under-reaction left behind by the newswatchers'.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Fangming Xu https://orcid.org/0000-0001-8984-0476
Liyi Zheng https://orcid.org/0000-0002-7054-755X

ENDNOTES

[1] Fama and French (2008, 2016) confirm that the price momentum phenomenon remains one of the most persistent anomalies.

[2] Polk and Sapienza (2009, p. 187) state 'If the market misprices firms according to their level of investment, managers may try to boost short-run share prices by catering to current sentiment'.

[3] Under Hong and Stein's (1999) framework, newswatchers forecast future stock prices based on their private information but do not learn information from others via stock prices. Therefore, information diffuses slowly, which generates momentum profits for momentum traders who trade solely based on past stock prices, and the stock prices will correct the initial underreaction and accelerate in the short term.

[4] The investment strategy is to take a long position in the low-investment stocks and a short position in the high-investment stocks to generate positive abnormal returns (Cooper, Gulen, & Schill, 2008; Hou, Xue, & Zhang, 2020; Lam & Wei, 2011; Lyandres, Sun, & Zhang, 2008; Watanabe, Xu, Yao, & Yu, 2013). Titman, Wei, and Xie (2004) and Cooper et al. (2008) argue that the investment anomaly is because investors are too slow to incorporate the information implied in corporate investment into stock prices, thereby causing mispricing.

[5] Returns generated by the price-momentum strategy declined significantly in the past decade or so. For example, see the work by Hwang and Rubesam (2015) and Mclean and Pontiff (2016).

[6] In conditions in which the equity financing and catering channels work better, a firm's level of investment serves as a better indicator of mispricing.

[7] Kusnadi and Wei (2017) confirm the existence of both channels with international data.

[8] For example, rational models suggest that the profitability of momentum strategies may reflect risk compensation (Conrad & Kaul, 1998; Jiang & Zhang, 2013).

[9] It is not difficult to understand why the focus has long been on fundamentals, as Huang et al. (2019) argue that 'academic research and education are almost entirely fundamentals'.

[10] The other commonly used investment strategy is based on Cooper et al.'s (2008) investment-to-asset ratios. Hou et al. (2020)

show that the two investment measures generate similar results during 1967–2016.

[11] The independent double-sorting method provides better controls in our study because the trailing 6-month returns are similar within the investment quintiles, and the I/A ratios are similar within the momentum quintiles (numbers are untabulated). In robustness tests, we also use sequential double-sorting, and we find similar results.

[12] In a latest study, Hou et al. (2020) replicates the Jegadeesh and Titman's (1993) momentum strategy and Lyandres et al.'s (2008) investment strategy for the period of 1967–2016. Our results are similar to their findings.

[13] We obtained the bear and bull turning points from Nyberg (2013), where the bear market starts between the month following the peak point and ends by the trough points, and vice versa for the bull market. The bear market periods over our whole sample period include: February 1966–September 1966; December 1968–June 1970; January 1973–September 1974; January 1977–February 1978; December 1980–July 1982; July 1983–May 1984; September 1987–November 1987; June 1990–October 1990; September 2000–February 2003; November 2007–February 2009, and the remaining periods are classified as the bull market periods.

[14] 'After the dismal performance of momentum in the last 10 years, some could argue it is a dead anomaly' (Barroso & Santa-Clara,-2015, p. 112).

[15] Polk and Sapienza's (2009) model is also built on the intuition of Stein's (1996) short-horizons model. Different from Baker et al. (2003), Polk and Sapienza (2009) focus on the catering theory and assume that all firms are financially unconstrained.

[16] Baker et al. (2003) explain that using the established KZ index, as opposed to building an equity dependence measure from scratch, also minimizes any concerns about data mining.

[17] Baker and Wurgler's sentiment index is obtained from Jeffrey Wurgler's NYU webpage: http://people.stern.nyu.edu/jwurgler/. The University of Michigan sentiment index is downloaded from the University of Michigan Surveys of Consumers website: http://www.sca.isr.umich.edu/.

[18] We use the book value of equity from the prior fiscal year end and skip 6 months before calculating returns to allow for the delay of financial statement releases.

[19] The construction of breakpoints of the size decile portfolios, book-to-market decile portfolios, and 5×5 size and book-to-market portfolios are based on Fama and French's (1992) method, which is obtained from Kenneth French's online data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[20] The definition of the 12-industry classification is obtained from Kenneth French's online data library.

[21] Pástor and Stambaugh (2003) argue that the liquidity risk factor accounts for half of the payoffs to a momentum strategy.

[22] We collect monthly returns of most of these risk factors from Kenneth French's website. We obtain the monthly returns of the liquidity factor of Pástor and Stambaugh (2003) from the Wharton Research Data Services (WRDS).

[23] The monthly returns of the momentum factor are collected from Kenneth French's website, and the monthly returns of the I/A factor are provided by Lu Zhang.

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